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Technical Note

Multiple sparse volumetric priors for distributed EEG source reconstruction

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ABSTRACT

We revisit the multiple sparse priors (MSP) algorithm implemented in the statistical parametric mapping software (SPM) for distributed EEG source reconstruction (Friston et al., 2008). In the present implementation, multiple cortical patches are introduced as source priors based on a dipole source space restricted to a cortical surface mesh. In this note, we present a technique to construct volumetric cortical regions to introduce as source priors by restricting the dipole source space to a segmented gray matter layer and using a region growing approach. This extension allows to reconstruct brain structures besides the cortical surface and facilitates the use of more realistic volumetric head models including more layers, such as cerebrospinal fluid (CSF), compared to the standard 3-layered scalp-skull-brain head models. We illustrated the technique with ERP data and anatomical MR images in 12 subjects. Based on the segmented gray matter for each of the subjects, cortical regions were created and introduced as source priors for MSP-inversion assuming two types of head models. The standard 3-layered scalp–skull–brain head models and extended 4-layered head models including CSF. We compared these models with the current implementation by assessing the free energy corresponding with each of the reconstructions using Bayesian model selection for group studies. Strong evidence was found in favor of the volumetric MSP approach compared to the MSP approach based on cortical patches for both types of head models. Overall, the strongest evidence was found in favor of the volumetric MSP reconstructions based on the extended head models including CSF. These results were verified by comparing the reconstructed activity. The use of volumetric cortical regions as source priors is a useful complement to the present implementation as it allows to introduce more complex head models and volumetric source priors in future studies.

Introduction

In this note we present a new application of hierarchical or empirical Bayes for distributed EEG source reconstruction. We depart from the parametric empirical Bayesian (PEB) framework used in the Statistical Parametric Mapping software (SPM) package (Wellcome Trust Centre for Neuroimaging, London, UK). Within the framework, the multiple sparse priors (MSP) algorithm is the state-of-the-art inverse technique. Depending on the EEG data, the algorithm allows the automatic selection of multiple cortical sources with compact spatial support that are specified in terms of empirical priors (Friston et al., 2008).

In the present implementation of the MSP algorithm, multiple cortical patches of sources are constructed based on a source space of dipoles constrained to a cortical surface mesh (Mattout et al., 2007) and the field propagation of the surface patches is calculated based on a 3-layered scalp–skull–brain head model (Henson et al., 2009). Constraining the dipolar sources to a cortical mesh does not allow the reconstruction of brain activity besides the cortical surface. Moreover, it is not straightforward to use more complex head models that extend

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the 3-layered model with extra layers such as cerebrospinal fluid (CSF). Because the dipoles are located on the boundary between the CSF and the brain, they will either be located inside the CSF or brain compartment which does not satisfy the restrictions to the source space of commonly used numerical methods, such as the boundary element method (Mosher et al., 1999), finite difference method (Hallez et al., 2005; Vanrumste et al., 2001) or finite element method (Wolters et al., 2002), to properly calculate the dipole field propagation (Stenroos and Nenonen, 2012; Strobbe et al., 2014).

In this work, we propose a technique to construct volumetric regions based on a dipole source space restricted to gray matter, segmented from an anatomical MR image, and using a region growing technique. This approach allows the inclusion of more prior information about the anatomy and shape of the sources and does not require the extraction of the cortical surface. It opens up the possibility to use the MSP algorithm to reconstruct brain structures besides the cortical surface and facilitates the use of more realistic volumetric head models including cerebrospinal fluid (CSF) compared to the currently used 3-layered scalp–skull–brain head models.

To illustrate the volumetric MSP approach, we used realistic ERP datasets and anatomical MR images in 12 subjects. Based on the segmented gray matter for each of the subjects, cortical regions were created and introduced as source priors for MSP-inversion assuming two types of head models. For every subject, a 3-layered volumetric subject specific head model was constructed. Also extended 4-layered head models including CSF were built to investigate the influence of increasing the head model complexity. We compared with the present implementation by assessing the free energy corresponding with the reconstructions using Bayesian model selection for group studies (Rigoux et al., 2013; Stephan et al., 2009). The reconstructed activity was also compared with the results of previous studies using similar ERP datasets (Mijović et al., 2012).

In the first section of this paper, we will briefly present the PEB framework and the MSP algorithm. We will explain how we extended the currently used approach based on cortical patches to volumetric regions and subsequently describe how the different head models used in this study were constructed. Next, we explain how we compared the models using Bayesian model selection and verified the reconstructed activity. We conclude with a discussion of the benefits and potential of using volumetric source priors.

Methods

Distributed EEG source reconstruction

Assume that we represent the EEG measurements as a multivariate linear model involving a distributed source model with fixed positions and orientations (Dale and Sereno, 1992):

$$V = LJ + \epsilon \tag{1}$$

where $V \in \mathbb{R}^{N_c \times N_t}$ is the EEG dataset of N_c channels and N_t time samples, $J \in \mathbb{R}^{N_d \times N_t}$ is the amplitude of N_d current dipoles with fixed orientations, $\epsilon \in \mathbb{R}^{N_c \times N_t}$ is the zero mean Gaussian noise and $L \in \mathbb{R}^{N_c \times N_d}$ is the lead field matrix linking the source amplitudes in J to the electrical scalp potentials in V. The lead field matrix represents the forward model and embodies assumptions about the head model and the forward modeling technique that is used.

Because of the ill-posed nature of the EEG source reconstruction problem (Baillet and Garnero, 1997), we need to add prior information to find a unique solution. There are different techniques that allow this, such as the weighted minimum norm (WMN) solution (Hämäläinen and Ilmoniemi, 1994):

$$\hat{J} = \min_J \left(\left\| C_\epsilon^{-1/2}(LJ - V) \right\|^2 + \lambda \|WJ\|^2 \right). \tag{2}$$

This approach implicates minimizing an energy function, with C_ϵ as the prior covariance of the sensor noise, W as the weighting matrix including prior information of the source activity and with λ a hyperparameter that tunes the relative importance of the accuracy of the model $\left\| C_\epsilon^{-1/2}(LJ - V) \right\|^2$, and the regularization term $||WJ||^2$. Given that $(\lambda W^T W)^{-1} = C_J$, with C_J as the prior covariance of the sources (i.e., it embodies our assumptions about the interaction among the sources), the solution of this equation becomes (Grech et al., 2008; Phillips et al., 2005):

$$\hat{J} = \left(C_J\right) L^T \left[L\left(C_J\right)^{-1} L^T + C_\epsilon \right]^{-1} V. \tag{3}$$

It follows that the solution of Eq. (3) directly depends on C_ϵ and C_J.

Parametric empirical Bayes: multiple priors

Eq. (1) can also be expressed in the context of a two-level hierarchical parametric empirical Bayesian (PEB) model:

$$\begin{aligned} V &= LJ + \epsilon_1 \\ J &= \epsilon_2 \end{aligned} \tag{4}$$

with ϵ_1 and n_2 assumed to follow a Gaussian distribution with zero mean: $\epsilon_1 \sim N(0, C_\epsilon)$ and $\epsilon_2 \sim N(0, C_J)$. The covariance matrices C_e and C_J can be modeled as a linear combination of covariance components (Phillips et al., 2007):

$$\begin{aligned} C_\epsilon &= \lambda_1^{(1)} Q_1^{(1)} + \lambda_2^{(1)} Q_2^{(1)} + \ldots \\ C_J &= \lambda_1^{(2)} Q_1^{(2)} + \lambda_2^{(2)} Q_2^{(2)} + \ldots \end{aligned} \tag{5}$$

with $\lambda_1^{(1)}, \lambda_2^{(1)}, \ldots$ and $\lambda_1^{(2)}, \lambda_2^{(2)}, \ldots$, the hyperparameters that balance the various covariance components either at the first (sensor) or second (source) level (Phillips et al., 2005).

In the SPM–PEB framework, the hyperparameters are estimated using a variational Bayesian estimation scheme by optimizing the free energy (Friston et al., 2007) given the covariance components. As such, $C_\epsilon(\mu_1)$ and $C_J(\mu_2)$, with $\mu_1 = \{\lambda_i^{(1)}\}$ with $i = 1, 2, \ldots$ and $\mu_2 = \{\lambda_i^{(2)}\}$ with $i = 1, 2, \ldots$, can be calculated. It follows that the expectation of the source intensities J given V is equal to:

$$E[J] = C_J(\mu_2) L^T \left[L C_J(\mu_2) L^T + C_\epsilon(\mu_1) \right]^{-1} V \tag{6}$$

with $E[J]$ the expected value of J. Note that we obtain the same solution as in Eq. (3), with the difference that we can introduce multiple constraints or priors in the form of covariance components.

Multiple sparse priors algorithm

In the absence of prior information, we assume the same amount of prior variance on all sensors: $C_\epsilon = \lambda_1^{(1)} I_{N_c}$, where $I_{N_c} \in \mathbb{R}^{N_c \times N_c}$ is an identity matrix, and $\lambda_1^{(1)}$ is the sensor noise variance.

In the multiple sparse priors (MSP) algorithm (Friston et al., 2008), a weighted sum of N_p predefined source covariance candidate matrices is used, where each covariance matrix represents a potential activated area of the cortex:

$$C_J = \sum_{i=1}^{N_p} \left(\lambda_i^{(2)}\right) Q_i^{(2)}. \tag{7}$$

The hyperparameters $\left\{\lambda_1^{(2)}, \ldots, \lambda_{N_p}^{(2)}\right\}$ weight these covariance components and control the power allocated to each of them. Note that these components may embody different types of informative priors, e.g., different smoothing functions, medical knowledge, and fMRI priors (Henson et al., 2011).